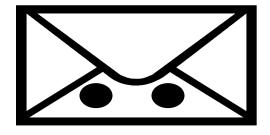
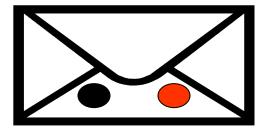
Two Envelopes Problem

- We have two envelopes:
 - E₁ has two black balls, E₂ has one black, one red
 - The red one is worth \$100. Others, zero
 - Open an envelope, see one ball. Then, can switch (or not).
 - You see a black ball. Switch?





Two Envelopes Solution

• Let's solve it.

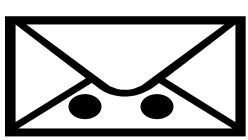
$$P(E_1|\text{Black ball}) = \frac{P(\text{Black ball}|E_1)P(E_1)}{P(\text{Black ball})}$$

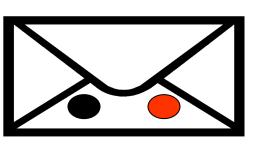
• Now plug in:

$$P(E_1|\text{Black ball}) = \frac{1 \times \frac{1}{2}}{P(\text{Black ball})}$$

$$P(E_2|\text{Black ball}) = \frac{\frac{1}{2} \times \frac{1}{2}}{P(\text{Black ball})}$$

So switch!





Q 1.1: Suppose P is false, Q is true, and R is true. Does this assignment satisfy

- (i) $\neg(\neg p \rightarrow \neg q) \land r$
- (ii) $(\neg p \lor \neg q) \rightarrow (p \lor \neg r)$
- A. Both
- B. Neither
- C. Just (i)
- D. Just (ii)

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Q 1.2: Let A = "Aldo is Italian" and B = "Bob is English". Formalize "Aldo is Italian or if Aldo isn't Italian then Bob is English".

- a. A V $(\neg A \rightarrow B)$
- b. A V B
- c. A \vee (A \rightarrow B)
- d. A \rightarrow B

Q 1.2: Let A = "Aldo is Italian" and B = "Bob is English". Formalize "Aldo is Italian or if Aldo isn't Italian then Bob is English".

- a. A \vee ($\neg A \rightarrow B$)
- b. A V B (equivalent!)
- c. A V $(A \rightarrow B)$
- d. A \rightarrow B

Q 1.3: How many different assignments can there be to $(x_1 \wedge y_1) \vee (x_2 \wedge y_2) \vee ... \vee (x_n \wedge y_n)$

- A. 2
- B. 2ⁿ
- C. 2^{2n}
- D. 2n

Q 1.3: How many different assignments can there be to $(x_1 \wedge y_1) \vee (x_2 \wedge y_2) \vee ... \vee (x_n \wedge y_n)$

- A. 2
- B. 2ⁿ
- C. 2²ⁿ
- D. 2n

Q 2.1: Which has more rows: a truth table on *n* symbols, or a joint distribution table on *n* binary random variables?

- A. Truth table
- B. Distribution
- C. Same size
- D. It depends

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- B. cold today
- C. is cold
- D. A & C

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Q 1.2: Smoothing is increasingly useful for n-grams when

- A. n gets larger
- B. n gets smaller
- C. always the same
- D. n larger than 10

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Q 2.1: What is the perplexity for a sequence of *n* digits 0-9? All occur with equal probability.

- A. 10
- B. 1/10
- C. 10ⁿ
- D. 0

$$PP(W) = P(w_1, w_2, \dots, w_n)^{-\frac{1}{n}}$$

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$$PP(W) = P(w_1, w_2, \dots, w_n)^{-\frac{1}{n}}$$

Q1-1: Which is true about feature vectors?

- A. Feature vectors can have at most 10 dimensions
- B. Feature vectors have only numeric values
- C. The raw image can also be used as the feature vector
- D. Text data don't have feature vectors

- A. Feature vectors can be in high dimen.
- B. Some feature vectors can have other types of values like strings
- D. Bag-of-words is a type of feature vector for text

Q1-2: Which of the following is not a common task of supervised learning?

- A. Object detection (predicting bounding box from raw images)
- B. Classification
- C. Regression
- D. Dimensionality reduction

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- B. The machine is given the training and test data for learning
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- C. In clustering, the training data also have labels for learning
- D. Supervised learning involves labeled data

- A. The labels are human inputs
- B. The machine should not have test data for learning
- C. No labels available for clustering

Q2-2: Which is true about unsupervised learning?

- A. There are only 2 unsupervised learning algorithms
- B. Kmeans clustering is a type of hierarchical clustering
- C. Kmeans algorithm automatically determines the number of clusters k
- D. Unsupervised learning is widely used in many applications

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Q 1.1: We have two datasets: a social network dataset S_1 which shows which individuals are friends with each other along with image dataset S_2 .

What kind of clustering can we do? Assume we do not make additional data transformations.

- A. k-means on both S₁ and S₂
- B. graph-based on S₁ and k-means on S₂
- C. k-means on S₁ and graph-based on S₂
- D. hierarchical on S₁ and graph-based on S₂

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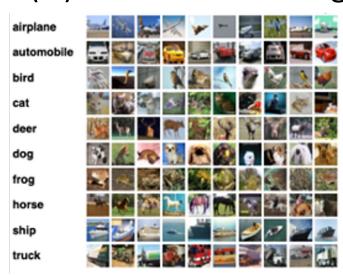
What kind of clustering can we do? Assume we do not make additional data transformations.

- A. k-means on both S₁ and S₂ (No: can't do k-means on graph)
- B. graph-based on S₁ and k-means on S₂
- C. k-means on S₁ and graph-based on S (Same as A)
- D. hierarchical on S₁ and graph-based on S₂ (No: S₂ is not a graph)

Q 1.2: The CIFAR-10 dataset contains 32x32 images labeled with one of 10 classes. What could we use it for?

(i) Supervised learning (ii) PCA (iii) k-means clustering

- A. Only (i)
- B. Only (ii) and (iii)
- C. Only (i) and (ii)
- D. All of them



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- **Q 1.2**: The CIFAR-10 dataset contains 32x32 images labeled with one of 10 classes. What could we use it for?
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- (i) Yes: train an image classifier; have labels)
- (ii) Yes: run PCA on image vectors to reduce dimensionality
- (iii) Yes: can cluster image vectors with k-means
- D. All of them

Q 2.1: Can we do t-SNE on NLP (words) or graph datasets?

- A. Never
- B. Yes, after running PCA on them
- C. Yes, after mapping them into R^d (ie, embedding)
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Q 2.1: Can we do t-SNE on NLP (words) or graph datasets?

- A. Never (No: too strong)
- B. Yes, after running PCA on them (No: can't run PCA on words or graphs directly. Need vectors)
- C. Yes, after mapping them into R^d (ie, embedding)
- D. Yes, after running hierarchical clustering on them (No: hierarchical clustering gives us a graph)

Q 2.1: When we train a model, we are

- A. Optimizing the parameters and keeping the features fixed.
- B. Optimizing the features and keeping the parameters fixed.
- C. Optimizing the parameters and the features.
- D. Keeping parameters and features fixed and changing the predictions.

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 (Feature vectors xi don't change during training).
- C. Optimizing the parameters and the features. (Same as B)
- D. Keeping parameters and features fixed and changing the predictions. (We can't train if we don't change the parameters)

 Q 2.2: You have trained a classifier, and you find there is significantly higher loss on the test set than the training set.
 What is likely the case?

- A. You have accidentally trained your classifier on the test set.
- B. Your classifier is generalizing well.
- C. Your classifier is generalizing poorly.
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• **Q 2.2**: You have trained a classifier, and you find there is significantly **higher** loss on the test set than the training set. What is likely the case?

- A. You have accidentally trained your classifier on the test set. (No, this would make test loss lower)
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- C. Your classifier is generalizing poorly.
- D. Your classifier is ready for use. (No, will perform poorly on new data)

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 is very likely, loss will usually be the lowest on the data set on which a
 model has been trained)
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- C. Your classifier is generalizing poorly.
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Q1-1: K-NN algorithms can be used for:

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- B Only regression
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Q1-3: Consider binary classification in 2D where the intended label of a point x = (x1, x2) is positive if x1>x2 and negative otherwise. Let the training set be all points of the form x = [4a, 3b] where a,b are integers. Each training item has the correct label that follows the rule above. With a 1NN classifier (Euclidean distance), which ones of the following points are labeled positive? Multiple answers.

- [5.52, 2.41]
- [8.47, 5.84]
- [7,8.17]
- [6.7,8.88]

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```
Nearest neighbors are
```

```
[4,3] => positive
```

Individually.

Q2-2: True or False Maximum likelihood estimation is the same regardless of whether we maximize the likelihood or log-likelihood function.

- A True
- B False

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- A True
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Q2-3: Suppose the weights of randomly selected American female college students are normally distributed with unknown mean μ and standard deviation σ . A random sample of 10 American female college students yielded the following weights in pounds: 115 122 130 127 149 160 152 138 149 180.

Find a maximum likelihood estimate of μ .

- A 132.2
- B 142.2
- C 152.2
- D 162.2

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- D 162.2

Q3-1: Which of the following about Naive Bayes is incorrect?

- A Attributes can be nominal or numeric
- B Attributes are equally important
- C Attributes are statistically dependent of one another given the class value
- D Attributes are statistically independent of one another given the class value
- E All of above

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Q3-2: Consider a classification problem with two binary features,

 $x_1, x_2 \in \{0,1\}$. Suppose P(Y = y) = 1/32, $P(x_1 = 1 | Y = y) = y/46$, $P(x_2 = 1 | Y = y) = y/62$. Which class will naive Bayes classifier produce on a test item with $x_1 = 1$ and $x_2 = 0$?

- A 16
- B 26
- C 31
- D 32

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Q3-3: Consider the following dataset showing the result whether a person has passed or failed the exam based on various factors. Suppose the factors are independent to each other. We want to classify a new instance with Confident=Yes, Studied=Yes, and Sick=No.

Confident	Studied	Sick	Result
Yes	No	No	Fail
Yes	No	Yes	Pass
No	Yes	Yes	Fail
No	Yes	No	Pass
Yes	Yes	Yes	Pass

- A Pass
- B Fai

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Yes	Yes	Yes	Pass

- A Pass
- B Fail

Consider the linear perceptron with x as the input. Which function can the linear perceptron compute?

(1)
$$y = ax + b$$

(2)
$$y = ax^2 + bx + c$$

- A. (1)
- B. (2)
- C.(1)(2)
- D. None of the above

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A. (1)

B. (2)

C.(1)(2)

D. None of the above

Answer: A. All units in a linear perceptron are linear. Thus, the model can not present non-linear functions.

Perceptron can be used for representing:

- A. AND function
- B. OR function
- C. XOR function
- D. Both AND and OR function

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Which one of the following is valid activation function

- a)Step function
- b) Sigmoid function
- C) ReLU function
- D) all of above

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Let $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$. Which of the following functions is NOT an element-wise operation that can be used as an activation function?

A
$$f(x) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

B $f(x) = \begin{bmatrix} \max(0, x_1) \\ \max(0, x_2) \end{bmatrix}$
C $f(x) = \begin{bmatrix} \exp(x_1) \\ \exp(x_2) \end{bmatrix}$
D $f(x) = \begin{bmatrix} \exp(x_1 + x_2) \\ \exp(x_2) \end{bmatrix}$

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D $f(x) = \begin{bmatrix} \exp(x_1 + x_2) \\ \exp(x_2) \end{bmatrix}$

Which output function is often used for multi-class classification tasks?

- A Sigmoid function
- B Rectified Linear Unit (ReLU)
- C Softmax function
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Suppose you are given a 3-layer multilayer perceptron (2 hidden layers h1 and h2 and 1 output layer). All activation functions are sigmoids, and the output layer uses a softmax function. Suppose h1 has 1024 units and h2 has 512 units. Given a dataset with 2 input features and 3 unique class labels, how many learnable parameters does the perceptron have in total?

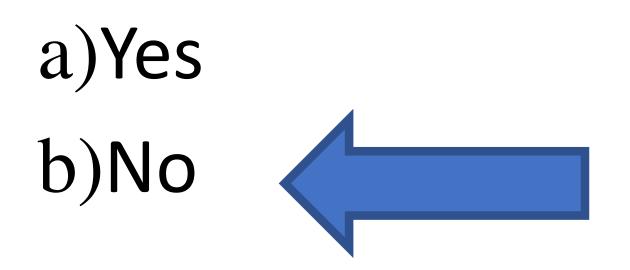
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1024 * 2 + 1024 + 512 * 1024 + 512 + 512 * 3 + 3 = 529411

Consider a three-layer network with **linear Perceptrons** for binary classification. The hidden layer has 3 neurons. Can the network represent a XOR problem?

- a)Yes
- b)No

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Solution:

A combination of linear Perceptrons is still a linear function.

Gradient Descent in neural network training computes the _____ of a loss function with respect to the model _____ until convergence.

- A gradients, parameters
- B parameters, gradients
- C loss, parameters
- D parameters, loss

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Suppose you are given a dataset with 1,000,000 images to train with. Which of the following methods is more desirable if training resources are limit but enough accuracy is needed?

- A Gradient Descent
- **B** Stochastic Gradient Descent
- C Minibatch Stochastic Gradient Descent
- D Computation Graph